SMAP REGULARIZED DUAL-CHANNEL ALGORITHM FOR THE RETRIEVAL OF SOIL MOISTURE AND VEGETATION OPTICAL DEPTH

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ABSTRACT

The Soil Moisture Active Passive (SMAP) mission was designed to acquire and combine L-band radar and radiometer measurements for the estimation of soil moisture (SM) with an average ubRMSE of no more than 0.04 m^3/m^3 volumetric accuracy in the top 5 cm for vegetation with water content of less than 5 kg/m^2.
Currently, a single-channel algorithm that uses the V polarized brightness temperature (SCA-V) is used to retrieve SM satisfying the defined requirements. Even though other alternatives were tested, SCA-V proved to be the best option for the retrieval of SM. In this work we show that by choosing suitable roughness parameters, the use of two polarizations (H and V), mixed dual-channel algorithm (MDCA), and an additional constraint, regularized DCA (RDCA), not only provides retrieved SM that satisfies the mentioned requirement but also allows for the retrieval of vegetation optical depth (VOD).

***Index Terms*—** SMAP, soil moisture retrieval, vegetation optical depth retrieval, dual-channel algorithm.

1. INTRODUCTION

The Soil Moisture Active Passive (SMAP) mission was designed to acquire and combine L-band radar and radiometer measurements for the estimation of soil moisture (SM) with an average ubRMSE of no more than 0.04 m^3/m^3 volumetric accuracy in the top 5 cm for vegetation with water content of less than 5 kg/m^2.

Since the SMAP mission collects single incident angle measurements providing two sets of measurements, the SMAP team had tested different algorithms for the retrieval of SM [1], mainly a single-channel algorithm that uses one of the observations to retrieve soil moisture and a dual-channel algorithm, which uses the two observations to retrieve not only SM but also VOD. Unfortunately, the SMAP team had shown that the dual-channel algorithm (DCA) leads to higher SM retrieval errors and, therefore it had adopted the SCA-V (uses V-polarized brightness temperature) as the baseline algorithm, depriving the mission of the ability to provide a trusted VOD.

The baseline algorithm uses the zero-order approximation of the radiative transfer equations, known as the τ-ω emission model [2]. To simulate L-band emission of soil-vegetation systems our model assumes a prior value of the scattering albedo and roughness parameters based on land cover type and also an estimate of VOD based on Normalized Difference Vegetation Index (NDVI) climatology [1]. In this study, we will focus on the selection of the roughness parameters, which have been a focus of study for several authors [3, 4 and 5].

The retrieval of VOD is of great value for the SMAP team not only because it will reduce the source of errors on the retrieval of SM (reduces the amount of assumed parameters) but also has significant importance to the science community since it will provide valuable information about the vegetation state.

Recent efforts to retrieve SM and VOD from SMAP data have been successful [3]. The author in [3] uses a multi-temporal dual channel algorithm (MT-DCA), which assumes that VOD changes more slowly than SM and can be assumed almost constant between every two consecutive overpasses. In addition, the MT-DCA approach allows for the retrieval of a single temporally constant value of the scattering albedo per pixel.

In this presented work we show that by choosing suitable roughness parameters, the use of the two polarizations (H and V), mixed dual-channel algorithm (MDCA), and an additional constraint, regularized DCA (RDCA), can not only provide retrieved SM that satisfies the mentioned SMAP requirement but also allows for the retrieval of VOD.

2. SINGLE AND DUAL-CHANNEL ALGORITHM

The SMAP baseline algorithm SCA-V that uses the V-polarized observed brightness temperature TB_V^{obs}, looks to minimize the

Table 1: Statistics performance comparison for the different algorithm under study.

Algortihm	ubRMSE (m^3/m^3)	Bias (m^3/m^3)	R (m^3/m^3)
SCA-V	0.038	-0.002	0.816
DCA	0.049	0.038	0.730
MDCA (a)	0.042	0.004	0.725
MDCA (b)	0.038	-0.015	0.777
RDCA	0.038	-0.014	0.775

cost function

$$F(SM) = \left[TB_V^{sim}(SM) - TB_V^{obs}\right]^2 \quad (1)$$

where TB_V^{sim} is the V-polarized simulated brightness temperature. To simulate the L-band emission of the soil-vegetation system the SMAP team uses the zero-order approximation of the radiative transfer equations, known as the τ-ω emission model [2]. In addition, several parameters need to be assumed, a prior value of the scattering albedo based on land cover, an estimate of VOD based on Normalized Difference Vegetation Index (NDVI) climatology and roughness parameters based on land cover as well as the clay fraction and land temperature to determine the soil dielectric constant.

An alternative approach is to use the DCA which simultaneously retrieves the SM and VOD τ by minimizing the cost function

$$F_D(SM,\tau) = \left[TB_V^{sim}(SM,\tau) - TB_V^{obs}\right]^2 + \left[TB_H^{sim}(SM,\tau) - TB_H^{obs}\right]^2 \quad (2)$$

where TB_H^{sim} is the H-polarized simulated brightness temperature. To date the DCA has been outperformed by the SCA-V. Indeed, the current DCA algorithm does not meet the SMAP accuracy requirement and therefore limits the SMAP mission for providing a reliable VOD.

To improve the DCA we focus our attention on the selection of the roughness parameters which were the focus of study for several authors [3, 4, 5]. The roughness characteristics of soil are introduced in the τ-ω emission model by means of the reflectivity

$$\Gamma_p(\theta) = [(1-Q)\Gamma_p^*(\theta) + Q\Gamma_q^*(\theta)]e^{\left(-h\cos^N(\theta)\right)} \quad (3)$$

where Q, h, and N are the roughness parameters and $\Gamma_p^*(\theta)$ is the reflectivity of the flat surface, the index *p* and *q* account for the polarization V or H. The current SMAP SCA-V and DCA assume $N = 2$, the coupling factor $Q = 0$ and $h = 0.01$ mm^{-1}s where *s* is the root-mean-square of the surface height [1].

In [3 and 4] an alternative model for the selection of the roughness parameter was proposed. Wigneron et al. [3] developed an empirical power function between *h* and *s* based on the PORTOS-1993 experimental data, given by

$$h = \left(\frac{0.9437s}{0.8865s + 2.2913}\right)^6 \quad (4)$$

Further, Lawrence et al. [4], based on simulated data, found that the coupling factor *Q* could be related to the *h* parameter using

Table 2: Current and suggested albedo values for different type lands.

Type land	Current albedo value	Suggested new value
Grassland	0.05	0.09
Cropland	0.05	0.062
Shrub open	0.05	0.09
Cropland/natural mosaic	0.062	0.14

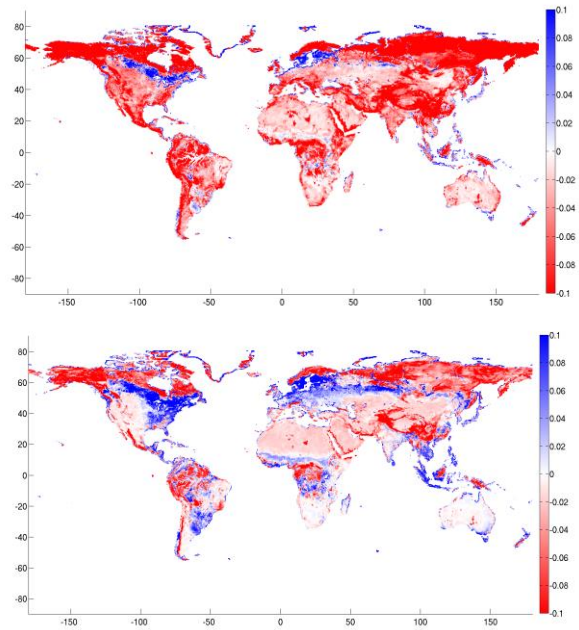


Figure 1: Map differences between SCA-V and DCA (top) and SCA-V and MDCA (bottom) for a full seasonal cycle. The maps show that the wet bias exhibited by DCA has been reduced by MDCA. The observed geographical pattern is being investigated.

the linear equation

$$Q = 0.1771\,h \quad (5)$$

That new parametrization of the roughness effect was validated by several authors and widely used in the literature [5, 7].

In this study we adopted this alternative parametrization (4) and (5) and $N = 2$ leading to the mixed dual-channel algorithm (MDCA) and its statistical performance was compared against the baseline SCA-V and current DCA, see Table 1. We see that the MDCA (a) outperforms DCA but falls short of meeting the requirements with an ubRMSE = 0.042 m^3/m^3 and that SCA-V still shows the best performance.

By observing the in situ data and discussing with the authors of [6], who provides global maps of albedo, we decided that tuning the albedo for some land type classes was appropriate. Table 2 displays the current values used by the SMAP team and the proposed new values. Table 1 shows that after adjusting the omega values the performance of MDCA (b) improved with an ubRMSE = 0.038 m^3/m^3, similar to the ubRMSE for SCA-V.

Table 3: Global SM differences statistics in m^3/m^3 for Figure 1. We compered the mean, mean absolute bias and Std of differences.

	Mean	MAbias	Std
SCA-V - DCA	-0.064	0.070	0.073
SCA-V - MDCA	-0.014	0.042	0.062

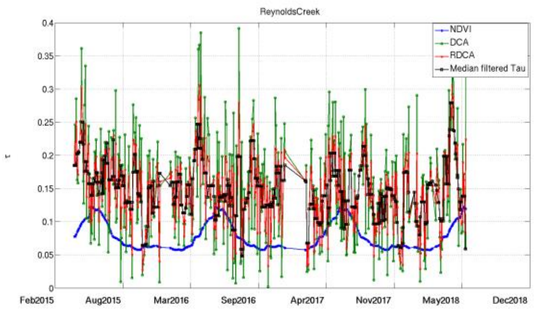


Figure 2: Display of NDVI tau used in the SCA-V retrieval, retrieved τ (VOD) by MDCA, the median filtered MDCA τ and the RDCA τ at the Reynolds Creek core validation site.

In Figure 1 we show the difference SCA-V minus DCA and SCA-V minus MDCA. We see, that overall, the wet bias with respect to SCA-V was reduced by MDCA. Current work in progress is trying to determine the cause of the geographical pattern of the observed differences. We hope to be able to give more insight on this issue in the final paper. Table 3 displays the mean, standard deviation (Std) and ubRMSD and shows that MDCA is providing a solution closer to the SCA-V solution.

3. REGULARIZED DUAL-CHANNEL ALGORITHM

Figure 2 displays the MDCA retrieved τ (green line, o mark) and the NDVI τ used in the SCA-V. It can be seen that the retrieved τ is in general higher that the NDVI τ but it can also be observed that the MDCA τ is temporally very noisy which is caused by the nature of the cost function with several local minima and a flat area of low cost function values. To reduce the high variability of τ, which is expected to vary slowly over time, we propose to solve a new minimization problem, a regularized DCA. The new cost function contains an additional constraint

$$F_{RDCA}(SM,\tau) = \left[TB_V^{sim}(SM,\tau) - TB_V^{obs}\right]^2 + \left[TB_H^{sim}(SM,\tau) - TB_H^{obs}\right]^2 + \lambda^2(\tau-\tau^*)^2 \quad (6)$$

to the MDCA cost function with a regularization parameter λ. The minimization process forces the retrieval algorithm to converge to a solution close to an expected value τ^*. In our implementation τ^* is the resulting τ after applying a temporal median filter over the MDCA τ (black line, □ mark in Figure 2).

The selection λ is crucial for the performance of the RDCA. To select the λ that provides the best performance we study the sensitivity of ubRMSE, bias and correlation as a function of λ. Figure 3 shows that the minimum ubRMSE can be obtained by setting λ = 16 and that the RDCA meets the SMAP requirement for all λ<80. Figure 2 (red line, x mark) displays the retrieved τ using RDCA with λ=16, resulting in a smoother temporal τ as was expected. Table 1 (bottom row) shows the statistical parameters for RDCA. It shows that the statistics for RDCA performance do not vary after regularization is applied. In other words, the performance of MDCA (b) and RDCA retrieving SM do not change after regularization, but a slow variant VOD is obtained.

4. ASSESSMENT

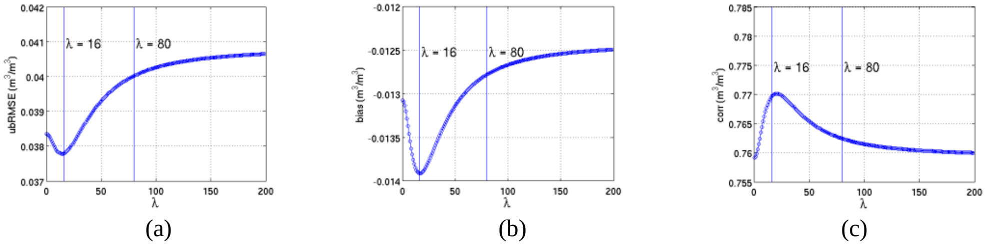
The SMAP mission validates the accuracy of the data using several sources of information. Among them are core validation sites, which provide the ground-based data in a timely manner to the SMAP project, and sparse networks such as the USDA Soil Climate Analysis Network (SCAN), the NOAA Climate Research Network and the Oklahoma Mesonet.

In section 2 and 3 we showed how the MDCA and RDCA compare at the core validation sites and both of them meet the SMAP mission requirements.

The assessment over the sparse networks requires the existence of global SM retrieval which it is only available for the MDCA. We are not able to provide an assessment over the sparse networks for the RDCA since it has not been implemented in the production code at this time. Table 4 displays the assessment report over the sparse networks using 38 months of SMAP SM data. The table compares the accuracy of MDCA against SCA-V and DCA. We display ubRMSE, bias, mean absolute bias (MAbias) and correlation (R) for several land types. We observe that SCA-V still outperforms the other two algorithms but we can also see that MDCA shows a significant improvement with respect to DCA.

We expect to have the RDCA assessment over the sparse networks by the time the final version of the paper is submitted.

Sensitivity with respect to *λ*



(a) (b) (c)

Figure 3: Performance of DCA algorithm as a function of λ. a) ubRMSE vs λ. b) bias vs λ. c) Correlation vs λ. We see that the minimum ubRMSE can be obtained for λ = 16 and that the RDCA meets the SMAP requirement for all λ<80.

Table 4: Sparse Network assessment. 38 months of data was used to compare the accuracy of MDCA with SCA-V and DCA. We displays ubRMSE, bias and, mean absolute bias (MAbias) for several land types.

Land type	ubRMSE(m^3/m^3)			Bias (m^3/m^3)			MAbias (m^3/m^3)			R (m^3/m^3)		
AM	**SCA-V**	**MDCA**	**DCA**	**SCA-V**	**MDCA**	**DCA**	**SCA-V**	**MDCA**	**DCA**	**SCA-V**	**MDCA**	**DCA**
Evergreen needleleaf forest	0.029	0.039	0.047	0.033	0.062	0.12	0.044	0.063	0.12	0.696	0.662	0.5
Mixed forest	0.057	0.058	0.066	0.005	-0.014	0.043	0.046	0.047	0.06	0.647	0.622	0.596
Open shrublands	0.04	0.044	0.049	0.001	0.012	0.05	0.045	0.048	0.068	0.553	0.553	0.53
Woody savannas	0.056	0.066	0.071	0.035	0.047	0.106	0.076	0.086	0.121	0.741	0.55	0.496
Savannas	0.031	0.03	0.039	-0.008	-0.002	0.013	0.044	0.045	0.053	0.877	0.859	0.862
Grasslands	0.05	0.053	0.058	-0.026	-0.016	0.035	0.059	0.06	0.07	0.693	0.674	0.64
Croplands	0.065	0.065	0.071	-0.012	-0.021	0.032	0.083	0.082	0.089	0.613	0.556	0.522
Crop/Natural vegetation mosaic	0.06	0.059	0.07	0.015	-0.029	0.08	0.075	0.082	0.104	0.689	0.686	0.54
Barren/ Sparse	0.022	0.024	0.029	0.014	0.027	0.058	0.031	0.039	0.06	0.591	0.594	0.543
Average	**0.046**	**0.049**	**0.056**	**0.005**	**0.007**	**0.06**	**0.056**	**0.061**	**0.083**	**0.678**	**0.64**	**0.581**

5. CONCLUSION

In this work we have shown that a modified DCA algorithm, by choosing a suitable set of roughness parameters and adjusted albedo values, allows for an accurate retrieval of SM and a reliable VOD τ.

6. ACKNOWLEDGMENT

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